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Enhancing City Sustainability through Smart Technologies: A Framework for Automatic Pre-Emptive Action to Promote Safety and Security Using Lighting and ICT-Based Surveillance

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Abstract: The scope of the present paper is to promote social, cultural and environmental sustainability in cities by establishing a conceptual framework and the relationship amongst safety in urban public space (UPS), lighting and Information and Communication Technology (ICT)-based surveillance. This framework uses available technologies and tools, as these can be found in urban equipment such as lighting posts, to enhance security and safety in UPS, ensuring protection against attempted criminal activity. Through detailed literary research, publications on security and safety concerning crime and lighting can be divided into two periods, the first one pre-1994, and the second one from 2004–2008. Since then, a significant reduction in the number of publications dealing with lighting and crime is observed, while at the same time, the urban nightscape has been reshaped with the immersion of light-emitting diode (LED) technologies. Especially in the last decade, where most municipalities in the EU28 (European Union of all the member states from the accession of Croatia in 2013 to the withdrawal of the United Kingdom in 2020) are refurbishing their road lighting with LED technology and the consideration of smart networks and surveillance is under development, the use of lighting to deter possible attempted felonies in UPS is not addressed. To capitalize on the potential of lighting as a deterrent, this paper proposes a framework that uses existing technology, namely, dimmable LED light sources, presence sensors, security cameras, as well as emerging techniques such as artificial intelligence (AI)-enabled image recognition algorithms and big data analytics and presents a possible system that could be developed as a stand-alone product to alert possible dangerous situations, deter criminal activity and promote the perception of safety thus linking lighting and ICT-based surveillance towards safety and security in UPS.

Keywords: smart sustainable cities; smart lighting; lighting design; crime prevention through environmental design (CPTED); social sustainability; artificial intelligence; big data

1. Introduction

Cities play a central role in strategic social sustainable development. The sense of safety and crime prevention constitute two, amongst a few, key elements for the sustainability and resilience of contemporary cities [1]. Since the early 1990s, the sustainability of cities has been associated with their capacity to be hubs of innovation that deploy Information and Communication Technology

(ICT) towards transforming contemporary social life, which transforms in many ways. For its healthy transformation and its inhabitants' well-being, however, safety must be a city's imperative attribute and demand, especially in times where the crime rate in contemporary metropolises is increasing exponentially.

The increasing crime rate in contemporary cities has to take advantage of the rapid advancements of ICT. These advancements include their omnipresence through data sensing, data processing, cloud/fog computing and wireless communication networking [1]. "Smarter cities [is] a class of cities which is viewed as future visions of smart cities and it is characterised by an ever-growing embeddedness and pervasion of ICT into the very fabric of the city." The way the term 'smarter' is used in this study does not refer to the further definition of the term in this source; namely 'smarter cities' due to the magnitude of ICT and the extensiveness of data with regard to their application and use across urban systems and domains. Smarter as a term in this study refers to the real-time data generation and in the way a combination and richness of technological ecology is at play. The notion of smarter as opposed to smart, cities will further encounter and contribute to the resolution of social issues deploying the combination of networking and infrastructures that can even involve citizens' bodies [2], but above all real-time data generation and the Internet of Things (IoT), using big data analytics as a critical enabler.

The uncontrollably increasing crime rate in contemporary metropolises is a wicked problem [3]. Copper lists a number of traits that classify a problem as wicked. One of the most crucial traits is its symptomatic association with another problem [4]. In Copper's words, "Any wicked problem could be viewed as a symptom of another problem". According to Birbi [5], contemporary cities are the key generators of social vulnerability and insecurity. As such, crime is associated with social inequity, unemployment, and domestic violence in a broader context of unsustainable societies.

As wicked, the problem of increasing crime rate is seeking nonlinear and innovative methodologies. These innovative methodologies must come from a transdisciplinary collaboration towards theory building, beyond the expected urban planning that up until recently has been exclusively responsible for the creation of urban public space (UPS). To date, there are two major and potentially complementary ways of dealing with crime in contemporary metropolises. The first involves psychologists, sociologists, medical professionals, and communities and is smoother, which we consider a way of looking into the cause, omitting the symptom. The second could be classified as confrontational, more drastic, and punitive involving police and justice. It involves stop-and-search activities by the police, the increase of police officer numbers, and the increase and the toughness of sentences, which we consider a way of treating the symptom, and not the cause approach. The former is achieved by analyzing the phenomenon qualitatively by working with people (communities, offenders, victims, police officers, etc.) towards unearthing the more subjective dimensions of the problem, the latter—by inventing technologies that can invigilate people and places towards ensuring their safety.

The present study attempts to bridge the discrepancy between smart and sustainable with safety as the core issue, as a result of the fact that smart and sustainable must be complementary and not contradictory features of a city, as it has often been the case [5]. Smart cities of a past paradigm, and not smarter that take full advantage of big data analytics, can only be "panaceas for solving the kind of wicked and intractable problems that characterize the urban domain" [1] accompanied by novel applications and services [6,7]. Urban lighting is a major source of energy consumption [8] and affects biodiversity [9,10], scientific research through light pollution [11], human well-being as well as health [12,13]. As such, urban lighting is a major player in all the factors that determine urban sustainability.

We propose an ICT-based framework that connects place (potential crime scenes) and space (spatial characteristics and perception) to dynamically improve the spatial characteristics of potential crime scenes towards deterring and discouraging crime by controlling lighting parameters. Its main aim is to contribute to the reduction and disruption of crime incidents, by investigating their connection to UPS, by controlling the lighting conditions and by deploying innovative ICT-based surveillance, which accounts for a highly synergistic effect on sustainable development [14], as well as smart

technologies that, by default, make a city safer [15]. The proposed framework considers data as an asset, where the extent of data and knowledge goes beyond expert forensic analysis. Even public sentiment posted on social media about the urban space can serve as a goldmine while investigating the safety of a place and space; the associated domains are well explored by different research groups within Anglia Ruskin University, such as Cortesi et al. focusing on natural language processing (NLP) and Kaiser et al. regarding crowd detection [16,17].

The structure of the paper follows the transdisciplinary nature of the groups of specialists that conceived of the idea and contributed to it. Namely, sections two and three, coming from an architect's bias, deal with the associations between UPS, spatial qualities of public space, potential crime place characteristics and safety. The smart city is defined, as well as the relation of UPS to crime.

The fourth section emerges from the bias of a lighting specialist, who is also an architect, that offers insights into lighting qualities that can indirectly affect crime in terms of its use as a deterrent and as a promotional measure for increasing the feeling of safety in a city. Lighting parameters are discussed and previous studies linking lighting to increase or decrease of crimes are analyzed.

The fifth section involves the main proposal and adds a data scientist bias. That is the creation of a framework to tackle the issues described in the previous sections. This framework involves the use of ICT and big data to decide upon the dynamic change of lighting parameters, so as to deter criminals and prevent crimes. The final sections provide a discussion on parameters that have to be dealt with, regarding data safety, personal information safety, cybersecurity and mostly face the ethics behind possible vulnerabilities of the proposed framework. The paper concludes with future possibilities and stakeholders that can undertake and develop the framework as a working prototype.

2. The Smart City and Crime

Urban public space is conflictual, multifaceted and complex [18]. This paper perceives crime as a conflictual, multifaceted, and complex problem that demands analogous articulation and management. The involvement of the role of space in crime, alongside the cause and symptom handling, is a creative and effective way of handling the problem overall.

The complexity and the systemic nature of crime in cities as a wicked problem dissolves the distinction between the two different approaches to the smart city. Namely, from a rather recent literature review [19] on smart sustainable cities of the future, two different approaches to the smart city are defined:

- (a) the technology-oriented approach, i.e., platforms, applications and model;
- (b) the people-oriented approach, i.e., stakeholders, citizens, knowledge, services.

In the present paper, our approach is addressed to a smarter city, not due to a soft or a harsh approach to either looking into the social derivations of inequity or by an increase of police force, surveillance and punitiveness, neither through a technology-centered or people-oriented approach. Our proposal tries to integrate all the above into a framework that promotes sustainability in a smart city context. Angelidou not only shares this approach but also sustains that clear-cut approaches that are 'self-congratulatory' and do not develop on reviewing pitfalls and challenges, are not the way forward [20].

Furthermore, the specificity of this study lies in Townsend's definition of a city as smart, as the environment where ICT is combined with infrastructure, architecture, everyday objects, and even our bodies to address social, economic and environmental problems [2]. In our case, ICT is combined with infrastructure, architecture, everyday objects, and our bodies to address the major issue of crime in contemporary metropolises. The proposed framework embraces and integrates the technological visions of sentient computing, ambient intelligence, ubiquitous computing, the Internet of Things (IoT), geographical information systems (GIS), while at the same time taking into account measures so as to reduce environmental and health hazards that can be traced back to street lighting.

UPS, as the spaces in which crime in contemporary metropolises occurs, are loaded with clouds of data, allowing therein their monitoring both in terms of human presence (activities, behaviors, social dynamics), as well as their spatial characteristics (urban texture, building density, street geometry, urban furniture configurations, lighting and acoustics conditions). Before big data analytics advancements, smart frameworks for cities operated through the analysis, interpretation and evaluation of models. Nowadays, they can be evaluated in real time and respond to the needs of diverse stakeholders.

Promising examples can be found for artificial intelligence (AI)-enabled building information modelling (BIM), architectural elements analysis, defect detection, materials engineering, smart furniture, etc. [21–25]. Coupling imaging data with field surveys, Xu et al. introduced a machine-learning-based evaluation of land usage and defective policies based on the discrepancy between detected and simulated urbanizations. Machine learning techniques can be useful in spatial land allocation, as demonstrated by Zhao et al. [26,27].

Beyond their inherent high volume, variety, velocity, resolution and flexibility [28], big data analytics are “relational in nature, containing common fields that enable the conjoining of different data sets”. Hence, an appropriate toolkit for addressing crime-related problems in a multifaceted context of different data sets is necessary. Moreover, not only are they descriptive but they can be predictive, diagnostic and prescriptive [5]. The capacity of big data analytics through the use of sophisticated software applications and database management systems run by powerful machines can allow for gaining insights into various urban domains including public safety [29].

Lytras et al. stress the importance of “the intersection of ICT and GIS in urban spaces and innate social problems and the attention this intersection has acquired in the past ten years [30]. However, Angelidou warns that the possibility that ICT advances offer for the monitoring of UPS, “fall short in considering issues of privacy and security” [31]. Bibri and Krogstie point out that ICT advancements “fall short in considering, if not ignoring, design concepts and principles and planning practices of urban sustainability and their effects and benefits” [19]. Bibri adds that “the two landscapes of the smart city and the sustainable city are extremely fragmented on the technical and policy level” [1].

Despite being in its infancy, the booming interest in self-driving cars from academia such as Stanford University [32–34], Oxford University [35,36], as well as from the industry (such as Tesla, Google, Uber) coupled with the advancement in AI technology have made computer vision (CV) for road safety an emerging research trend. CV concentrates on replicating parts of the complexity of the human visual system and enabling computers to identify and process objects in images and videos in the same way that humans do. Deep learning, especially convolutional neural networks (CNN), is vastly applied to the field of image recognition that can aid in autonomous driving; an overview is presented in Fujiyoshi et al. [37]. The success of the ImageNet project has prompted many endeavors associated with self-driving technology using CV—real-time traffic light recognition [38], pedestrian detection [39]—just to name a few. The use of CV in a smart city context [40] finds its usefulness in vehicle recognition in traffic scenes [41], which could be extended to microscopic behavior analysis of pedestrians and cycle commuters in shared spaces [42]. CV is also deployed in a drone’s vision [43], which when paired with GIS [44] can present endless opportunities.

Moreover, deep facial recognition [45], gesture recognition [46], crowd detection [16], crowd behavior analysis [47], crime scene analysis [48], etc. using machine learning techniques have been subjects of great interest beyond computer science. The transdisciplinary advances within the AI domain have opened the door to automate bulks of information to be analyzed along with its context. Automation of context analysis already demonstrated success in chatbots using NLP [49,50], which may be further extended to context-aware image processing [51]. It is anticipated that progress made across the diverse fields will continue to improve with the fast-paced advances in machine learning, the scale of data and processing units along with other hardware components.

3. Space, Place and Crime

Research shows that the following risk evaluation indicators play a role: accessibility and escape routes used by offenders, physical vulnerability of potential targets, the presence of ‘social eyes’ exercising surveillance and control, visibility (e.g., lighting, layout of buildings, landscaping, etc.), involvement and responsibility of residents and the aesthetics of buildings and landscapes [52]. This research continues by analyzing previous research and assembles the most crucial observations concerning space, place and crime:

- Crime can be prevented by (a) a clear demarcation between public and private space, (b) eyes on the street, (c) continuous use of streets [53];
- The possibility of informal control by residents can create defensible space coupled with feelings of territoriality [54];
- Previous crimes can identify areas that are crime-prone, since offenders make rational choices and operate in areas they know [55].

In view of these studies, the physical environment always plays a secondary role, and its design is a prerequisite for crime motivation or crime prevention. We also identify the “visibility” indicator as one of the most important, since not only is it mentioned across studies, but it is a direct outcome of spatial and lighting design as we will show in the next section.

As the editors of *Order and Conflict in Public Space* explain in their book’s preface, public spaces have become a hot topic for debates and the press as they can potentially become spaces for transgression and deviant behavior, a phenomenon that also concerns contemporary societies, politicians, authorities, criminologists and urban space designers [56]. Karen Lumsden in the same volume, and more specifically in her essay ‘Boy racer culture and class conflict: urban regeneration, social exclusion, and the rights of the road’, uses the Lefebvrian triad of perceived, conceived and lived space to study the ways in which contemporary urban restructuring transforms the ways in which public space and the everyday life are revisited towards preventing crime. The psychology of fear generated in public space can be the reason why life in contemporary city centers can be unpleasant.

Extensive studies undertaken by contemporary scholars invest in strategies for the design of public space in contemporary cities that can contribute to crime prevention as a way of turning unsustainable cities into sustainable ones [57]. A great deal of research has been elaborated by experts on lighting on the importance to alleviate easy, naïve and straightforward appreciation that comes to the conclusion that more light at night-time in public spaces can reduce the fear of crime and the overall criminal activity [58]. The complexity of this correlation, ways from simplification, is what has given rise to the current research and the respective methodology proposed.

4. City Lighting and Crime

Lighting and its inference on crime are usually misunderstood by the public in the belief that more lighting refers to safer streets. This misconception is prevalent due to several studies showing that crime is reduced by improved street lighting and this improvement is usually attributed to intensity [59,60]. However, according to Marchant, this is not the case [61,62]. It should be apparent that each case differs from the next, as lighting depends highly on its adjacent spatial geometry, as well as the luminous source characteristics. It also has to be mentioned that all of the aforementioned studies were done before the advent of light-emitting diode (LED) technologies. That can further include the relationship of light and lighting qualities with spatial characteristics such as urban texture, building density, street geometry, vehicular and pedestrian circulation and transport, use (stop, gathering, passing), the thresholds and transitions between public and the private spaces, and function (commercial, residential, mixed use). In this view, Boyce [63] concludes that lighting can affect crime indirectly through two mechanisms. Firstly, by enabling people to recognize the intentions of others, see well all around and allow better surveillance. Secondly, by enhancing community confidence and increasing

the degree of informal social control. By adding increased reassurance of vulnerable groups, it is apparent that controlling light and its parameters can enhance city life in many ways [64–66].

Since lighting is composed of both quantitative and qualitative characteristics, such as intensity, uniformity, vertical semi-cylindrical illuminance, glare, color temperature and color rendering among others [67], the present research supports that each characteristic plays its own role in terms of crime prevention, when considering the design of the space that the lighting is situated at. For example, intensity of a light source, the luminaire design, and its placement in correlation with location can produce glare, while non-uniform lighting can create shadow spaces and low vertical semi-cylindrical illuminance that deprive pedestrians of facial recognition.

It is also the case that often fear of crime is mistaken as an indicator for criminal activity, which can direct to misinterpreted results. In supporting this, Welsh and Farrington [68] state that although there are no new studies linking the decrease of crime rates to improved lighting, all older studies have shown it to be true. Moreover, an analytical literature review supports that through a large body of evidence and empirical proof, crime prevention can be achieved through the design of the environment [69].

According to Painter [70], street lighting does not constitute a physical barrier to crime, although “it can only be effective if it alters the behavior and perceptions of the public, including potential offenders”. The increase of visibility, recognition of facial characteristics and increased lines of sight are some of the mechanisms through which lighting can contribute to reduce criminal activity and fear of crime. Since offenders prefer to remain unseen [71], the above factors play a crucial deterring role, as well as decrease the fear of crime since pedestrians are likely less at risk of surprises, whereas they can also identify potential threats due to increased view of facial expressions. This can be supported by the “broken windows” theory, in which George Kelling and Catherine Coles support that visible signs of crime, anti-social behavior and civil disorder create environments that encourage further crime and disorder, including serious crimes [72]. With this in view, inconsistencies in lighting, whether they refer to a damaged luminaire, or even inconsistent design that creates non-uniform lighting resulting in the succession of dark and fully lit areas, create a space that, both in the eyes of the public and criminals, can support criminal activity.

Other researchers have associated lighting with social inequities, and as such, lighting imposes another issue on potential criminal activities [73]. The reports of the LSE program “Configuring Light” confirm the fact that aesthetically pleasing lighting that corresponds to low luminous intensities and is perceived as “darker” (usually the outcome of carefully planned lighting) is found in affluent neighborhoods and upmarket developments. On the contrary, high intensity lighting with high correlated color temperature (CCT) is a feature mostly of social housing since it is calibrated for closed-circuit television (CCTV) surveillance and the prevention of anti-social behavior and crime. The above facts attribute to outdoor lighting a social aspect in the sense that the quality of lighting can provide space with social inequality traits that decreases the social sustainability of a city.

In general, artificial lighting is assessed through quantitative characteristics that are described in the International Standards EN12464-2:2014 “Light and Lighting. Lighting of Work Places. Outdoor Work places”, EN13201-1:2014 “Road Lighting–Part 1: Guidelines on selection of lighting classes” and EN13201-2:2016 “Road Lighting–Part 2: Performance Requirements” [74–76]. These guidelines provide information on proper luminance and illuminance on roads and vertical surfaces that ensure road and work safety. They also suggest the effects and quantity of glare from artificial light sources that can add up to disability glare, where a person cannot see properly due to the contrasting intensities, as well as the uniformity of lighting on horizontal surfaces and the solid angle emittance of the luminaire itself. While these guidelines were developed with energy efficiency and road safety in mind, they possess qualities that can positively influence the reduction of criminal activity and the fear of crime if used properly, thus promoting the sustainability of the city, not only in terms of energy efficiency, but also in terms of social security and safety. As we will support in the following paragraphs, lighting quality is a complex issue that depends on several factors in order to achieve specific goals.

Light intensity is a quantitative factor in the above guidelines that can also be assessed in qualitative terms. The promotion of general darkness (i.e., low light intensities) provides several benefits. First of all, it promotes environmental sustainability due to the fact that it minimizes impact on the environment and biodiversity. It also enhances the overall uniformity of lighting in given conditions, since there is less contrast between totally dark and lit areas. Finally, it does not highlight potential targets for criminal activity and as such, criminal activity is observed as reduced in areas with low lighting conditions.

To this day, there are contrasting studies concerning the amount of illumination and its correlation to crime [77] and this is probably due to the fact that these criminal studies do not consider lighting in qualitative terms, but only quantitatively and in ambiguous terms. In general, most studies refer to “improved lighting”, or “more lighting”, without providing technical details of the lighting schemes installed and it is therefore impossible to determine if the lighting scheme used in specific research had other qualities apart from larger intensities or denser concentration of luminaires. For example, Welsh and Farrington [68] provide evidence that improved lighting results in statistically significant lower odds of a crime being committed in the USA and the UK, while on the contrary, in other US and UK cities, Morrow and Hutton [78] and Steinbach et al. [79] did not find any significant correlation between crime rates and reduced lighting. The contrasting evidence can be traced back to the intricate qualities that the distribution of light has in a specific space. The correlation between lighting intensity and crime can therefore be determined as situational, as it can only be determined through specific cases and cannot be applied as a general rule of thumb. However, higher street light luminance usually reduces fear of crime, especially in women [80,81]. Table 1 shows relevant published studies on the effect of lighting on crime where the uncertainty described above is obvious.

Table 1. Published studies on the effect of improved lighting on crime.

Publication	Study Period	Location(s)	Results
[82]	1970–1973	Kansas City MO, USA	Sufficient lighting reduced violent crimes (−39%), robberies (−52%) and assaults (−41%) but did not reduce burglaries. Vehicle thefts increased (3%).
[83]	1977	USA	There is no significant statistical proof that road lighting affects criminal activity when considering possible crime dispersion. Possibly the uniformity of lighting reduces fear of crime.
[80]	1980–1990	London, UK	No changes in criminal activity were found and no changes in the feeling of safety.
[84]	1994	Glasgow, UK	Verified crime reduction (−14%).
[85]	1994	London, UK	Small reduction in crime and fear of crime.
[78]	2000	Chicago IL, USA	Increase of crime rate in all crime categories (21%).
[86]	2002	London, UK	Reduction in specific areas (−20%).
[87]	1974–1999	Atlanta GA, Milwaukee WI, Portland OR, Kansas City MO, Harrisburg PA, New Orleans LA, Fort Worth TX, Indianapolis IN, Dover UK, Bristol UK, Birmingham UK, Dudley UK, Stoke-on-Trent UK	In the USA, 4 out of 8 studies show that lighting has an effect on reducing crime, the other half that it does not. In the UK, all studies show that lighting affects crime and that improved lighting can reduce crime in some circumstances.
[88]	2011	Los Angeles CA, USA	Inconclusive on whether surveillance or common trust theory explain the relationship between lighting and crime.
[79]	2015	England and Wales, UK	No significant correlation between crime and lighting.
[89]	2012–2014	San Antonio TX, USA	Reported reduction in violent crimes in specific areas. All other crimes unaffected.
[90]	2019	New York NY, USA	Index crimes reduced (−36%).

The **uniformity of lighting** is a paramount characteristic for good quality lighting schemes. Not only is this lighting characteristic part of the International Standards and is quantifiable, but there

is evidence that high uniformity can be a factor for deterring criminal activity, since it promotes surveillance according to Crime Prevention Through Environmental Design (CPTED) [69]. As Morrow and Hutton suggest, brightly lit alleyways can provide fertile ground for criminals to pinpoint a target [78]. What “brightly lit” means is a lack of uniformity, a case where the adaptability of the human visual system cannot cope with the range of luminance in the visual environment and the brain interprets a specific luminance range. All areas that are outside this range are considered either too dark, or too bright to see. Therefore, when we have a case of brightly lit areas, it automatically means that there are darker areas as well, which could be used by criminals or for criminal activity. Moreover, published research from the Lighting Research Center (LRC) suggests that higher uniformity than the guidelines of the EN13201 provides a higher feeling of safety in a study concerning a parking lot [91]. This also applies to CCTV surveillance cameras, as they have low dynamic range sensors and cannot cope with low uniformity lighting. There are, however, cases where uniform lighting without surveillance can increase petty crimes such as vehicle thefts [82], since uniform lighting provides better visual information.

Semi-cylindrical illuminance, the average vertical illuminance on half of a cylindrical object at a specific height (i.e., a person’s head), is another lighting factor that can enhance safety and security. Though it is a metric that is used mostly for broadcast services, it is often used as a metric that promotes safety and security for outdoor lighting, since it corresponds directly to the recognizability of facial characteristics and thus intentions [76,92]. Furthermore, increasing semi-cylindrical illuminances greatly accounts for the reduction of fear of crime as several studies have shown [77].

Light glare can be a very important parameter when dealing with crime and fear of crime. While new luminaires that respect the European norms take into consideration glare and try to minimize it at the source, apart from non-refurbished luminaires, there is still a large portion of products that do not control glare and can be used in outdoor lighting, mainly in parks, pedestrian roads and squares. This poses a problem in crime prevention since glare can completely block the human visual system, resulting in both inability to adapt to darker visual stimuli, as well as increase in discomfort [93]. Since glare happens most of the time when looking at an unprotected light source or its reflection, the human visual system experiences a large amount of luminance in a very small portion of its cone of vision. This results in longer adaptation times and makes unsuspected targets vulnerable to attack. Glare can be addressed at the design phase by using glare-controlled luminaires and making sure that specular reflections are minimized.

Color rendering—commonly measured by the Color Rendering Index (CRI) metric—refers to the ability of a light source to accurately render colors. Light sources have varying accuracies depending on the technologies implemented. Whereas there is little relation to crime prevention, color rendering is a quality that can aid police, as well as informal surveillance and consequently deter criminal activity. The accurate perception of color is a factor that enhances recognizability. There are, however, certain drawbacks to using high-CRI luminaires apart from the higher installation and maintenance cost. Amber LED technology is gaining ground as opposed to white LED due to considerations of blue light regarding human health and light pollution [94]. Whereas white light covers most of the visible spectrum (400–780nm) resulting in high CRI, amber light focuses usually in the range between 550–750nm, discarding “cool” colors such as green, blue and magenta. This can lead to a variety of problems concerning crime prevention and mainly to the fact that accurate surveillance is compromised.

Other factors that influence the perception of lighting in external spaces include **subjective preferences** as suggested by Johanson et al. [95]. Clearness, strength, focus, brilliance, sharpness, softness, glare, warmth and of course dark or light are such subjective factors that most people can understand and evaluate. These factors can be traced by bipolar differentials and as such the perceived outdoor lighting quality tool (POLQ) was developed to address both the perceived strength of lighting (PSQ) and the perceived comfort of lighting (PCQ) [96]. While the reference of these factors is not directly related to crime, it would be beneficial to study the influence of different light sources on the

perception of crime. Finally, one of the most important factors that were found to play a part in the feeling of safety is the natural tendency to look at people approaching and identifying their intentions and facial characteristics [97] in which all factors mentioned above are of paramount importance since bad lighting quality can hinder facial recognition.

5. Framework for Combining Existing Technologies

In the previous sections, we discussed the relationships between crime and environment and crime and lighting. Our research supported that, although studies concerning crime prevention and lighting are inconsistent in their findings—several cases support that improved lighting can aid crime prevention, whereas others are inconclusive—there is fertile ground to elaborate on details in lighting that when controlled properly can possibly prevent criminal activity. This, however, cannot be applied without the integration of ICT that select and controls the appropriate lighting parameter dynamically according to the situation at hand. With data sensing, data processing platforms, cloud computing infrastructures and wireless communication networks embedded in urban systems, the quality of life of citizens can improve [98]. Bibri defines datafication as the process whereby a city is put in a quantified format so it can be structured and analyzed. This datafication can yield data from sensors deployed across urban environments so that crime-prone scenes can be noticed and tackled before crimes actually happen and thereby influence operations, functions, services, designs, strategies and policies. As described, the identified issues concerning the relationship between crime prevention and lighting can be categorized as shown in Table 2.

Table 2. Categorization of crime prevention factors according to crime prevention through environmental design (CPTED) and lighting parameters.

CPTED	Lighting Parameters
Natural surveillance	Increased horizontal illuminance
Natural access control	Increased vertical illuminance
Natural territorial enforcement	Increased semi-cylindrical illuminance
Maintenance (“broken window” theory)	Glare free
Activity support	Good Colour Rendering values
	High uniformity

While there are many studies that have used ICT for crime prevention [99], there are not many studies and proposals to incorporate ICT in street lighting with a main function to deter crime. Cho et al. developed a prototype methodology of a connected security lighting system that identifies a pedestrian’s smartphone via a Bluetooth beacon and increases luminance at the immediate area. In the event that a pedestrian does not have a Bluetooth device to be detected, an infrared sensor detects movement and increases luminance respectively [100]. Moreover, leveraging the successes of CV, this paper proposes a framework that can integrate the lighting parameters factoring the CPTED elements as highlighted in Table 2. The framework layout—as shown in Figure 1—comprises of three sections:

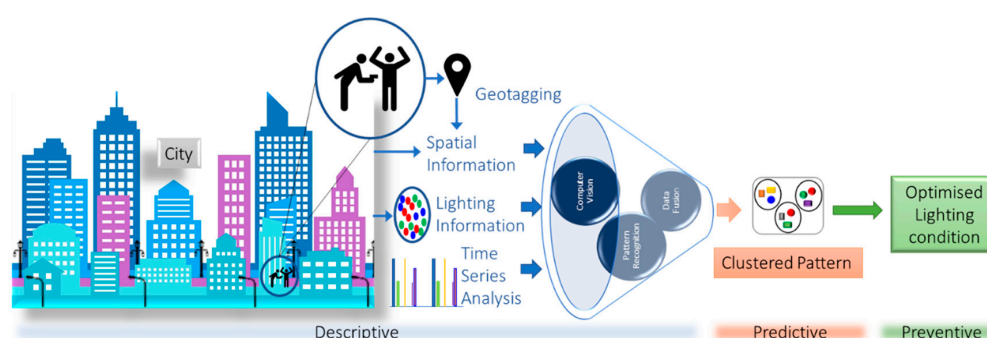


Figure 1. High-level architecture of artificial intelligence (AI)-enabled optimization of city lighting.

A descriptive model describes a system or other entity and its relationship to its environment. Data aggregation is the process in which raw data is gathered and expressed in a summary form. Data mining is the process of finding anomalies, patterns, and correlations within large data sets to predict outcomes. The first section can be defined as the descriptive model of the framework that utilizes data aggregation and data mining to search for similarities in the data, to find existing patterns and to develop the captivating subgroups in the major part of the data available. The next step, i.e., predictive model, can benefit from the insights perceived from summarizing retrospective data. Retrospective data gathering involves geotagging of the area and spatial information from GIS data (including satellite images) and/or surveillance cameras, as well as time series analysis of past crimes and criminal areas from a knowledge base, and lighting characteristics of installed luminaires.

The second section can be defined as predictive, to be informed by the descriptive analysis of real-world events within the city space and the relationships between factors responsible for them. Pattern recognition is the process of recognizing patterns by using a machine learning algorithm. It is the ability to detect arrangements of characteristics or data that yield information about a given system or data set. Cheng 2012 described data fusion as the process of integrating information from multiple sources to produce specific, comprehensive, unified data about an entity [101]. The recent advances are described elsewhere [102]. Building on the knowledge from retrospective data gathering as well as real-time data gathering using computer vision, pattern recognition and data fusion, the purpose of the predictive analysis is to support the stakeholders of a sustainable city to make an informed decision, which can be further extended to automate such decision-making.

The third section is defined as preventive and uses the analysis of the predictive model to influence dynamic changes in the lighting characteristics of the specific area.

However, to contribute within the problem space of this paper, the next generation of AI needs to enhance the context awareness of crime scenes. This paper proposes the next generation AI to be less artificial and more intelligent, so that it can understand and interpret the context of a scene and connect the crime scene with associated spatial and temporal components. Harnessing the recent successes in CV, this paper proposes the framework (Figure 1) that connects a crime scene with associated spatial and temporal elements; some of its low-level specifics are outlined in Figures 2 and 3.



Figure 2. Crime categorization using computer vision.

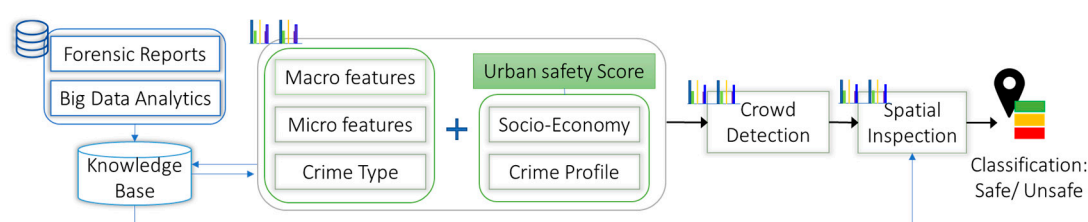


Figure 3. AI-powered localized vulnerability detection.

The spatial investigation will start with deep-learning-based CV to extract the features, where a feature is an individual measurable property or characteristic of a phenomenon being observed (Figure 2). The objective of the framework shown in Figure 2 also includes automatic categorization of a crime scene. Once trained (the training process involves finding a set of weights in the network or machine learning model that proves to be good, or good enough, at solving the specific problem), the predictive model should be able to correctly speculate from a real-time scene if a crime is happening and the required alert level of the crime, as suggested in Figure 2.

The next step is to develop an understanding of how a specific type of crime, along with its quantified internal representatives (Figure 2), links to the past states in a distributed space, that can inform the spatial inspection process (Figure 3). An example of such a temporal element would be enabling the connection between intention and action within the UPS using AI. For example, backtracking how the offender and the victim reached the crime scene using context-aware CV.

In the clustered pattern section (Figure 1), processing of the real-time data takes precedence since it defines the possible criminal actions. For example, if a metal object in the CV real-time data is correlated with a possible pattern of a knife or gun part and knowledge-base and geotagging data indicate a crime-prone area, then the possibility of a crime happening is high and the area lighting is signaled to elevate to its full intensity and higher CCT and CRI, so as to make identification easier and provide an alert status.

Localized vulnerability detection will use AI to process data such as forensic reports and big data analytics (Figure 3) and correlate them with spatial inspection. It is connected to a knowledge base that leverages existing knowledge on criminal activities in UPS that provides an “Urban Safety Score”, which is then provided to the crowd detection system (surveillance cameras, sensors, social media data) to ultimately classify in real time the area as safe or not. Along with data, the knowledge base is also continually informed using reinforcement learning so that the vulnerable regions are updated based on a holistic aspect.

It has to be noted that the above crime categorization and vulnerability detection are the main means of live prediction of crime. The preventive measures proposed in this paper concern the alteration of lighting characteristics to ensure that potential victims are alerted, while potential threats are targeted, thus reducing the possibility of committing a crime. While current LED technologies are praised for maximizing energy efficiency, they also provide easy access to a variety of control features that can be easily altered. LED luminaires can alter their intensity through dimming and can host a variety of different light sources within a single unit of housing with their corresponding features. An optimal luminaire for use in the proposed framework could host the following:

LED light sources of low CCT. Low CCT LEDs can be in the range of 1800–2200 K, with a spectral transmission ranging from 550 nm–700 nm. These sources will be used for the main area lighting and as such, low CCT ensures that they do not emit low wavelength radiation at the blue part of the visible spectrum, which is considered to affect human well-being [103], as well as causing light pollution [94,104]. Furthermore, narrow angle lenses (spot) should be used in these LEDs to maximize the beneficial light, minimize glare, and reduce obtrusive light (CIE150:2017).

LED light sources of high CCT. High CCT LEDs can be in the range of 5600–6500 K, with an effective spectral transmission ranging from 400–620 nm. These sources will be used for alarming purposes, as well as complementing spectral transmission and more importantly cylindrical illuminance—used for facial recognition—that the low CCT light sources will lack, since they will be installed in wide-angle lenses to provide a wider lighting distribution.

Processing unit with embedded light fidelity (LiFi) controllers, so that individual luminaires can form a communication network that will be used both for control and data communication.

Motion detectors, that can provide sensory information for dimming and on/off functions for maximizing energy efficiency and providing starting commands to a proposed framework.

The operating pattern of these luminaires is shown in Figure 4. It is clearly shown that each luminaire is controlled through a lighting processing unity (LPU) that communicates with other

similar luminaires and the clustered pattern through LiFi controllers. LPU is aware of the area and its classification as safe or unsafe to control probability of crime. The LPU provides control for specific power output to each LED group, so that it corresponds to specific needs. In the case where no motion is detected, the system is in the OFF state (or dimmed to a safety minimum depending on regulations). If motion is detected, real-time data are analyzed, and the possibility of crime calculated. In cases when the possibility is high, power is distributed to all LEDs to ensure high alertness and increased facial recognition. Information is passed on to adjacent luminaires to determine their state.

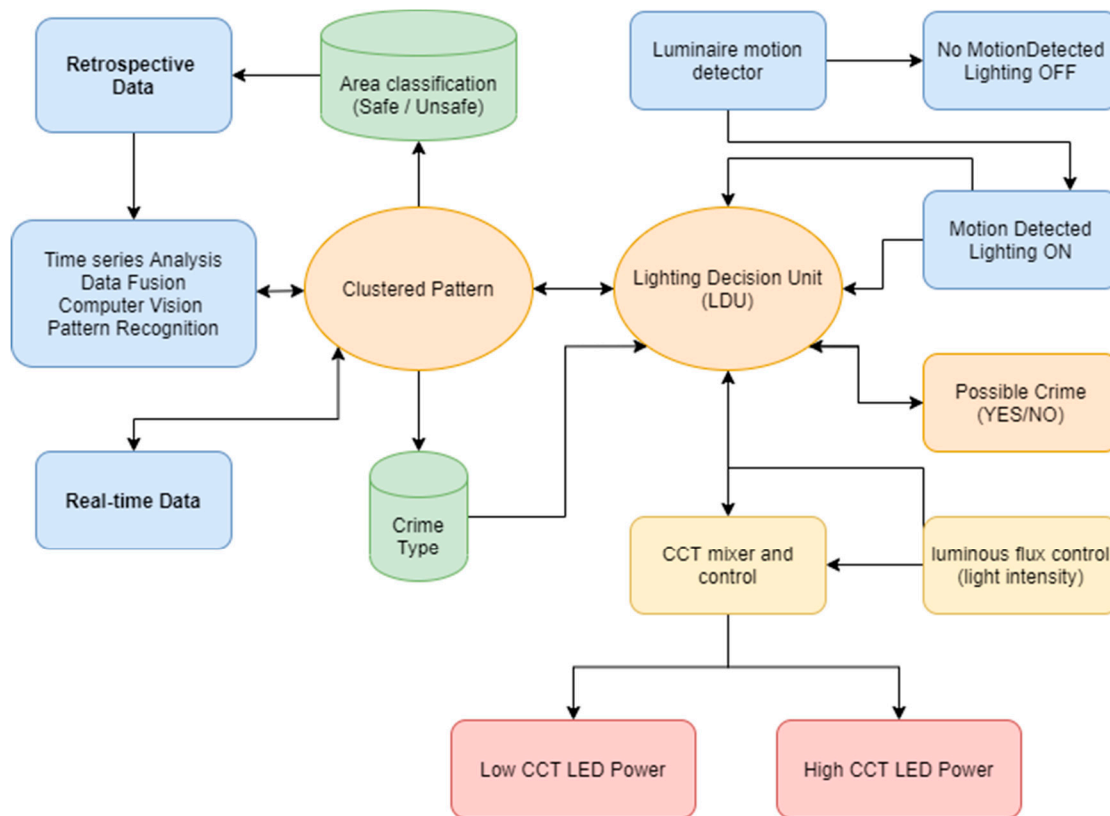


Figure 4. Logical diagram of preventive section operation.

6. Discussion

The relationship between crime, space, lighting, and ICT is a complex one. The multitude of variables involved, and the continuous feed of data generation suggest the use of integrated solutions. The proposed framework presented in this paper tried to connect the spatial characteristics of UPS and propose such solutions by acquiring data from a multitude of different data sources, analyzing and connecting them, providing real-time information to smart luminaires, so that they can alter their characteristics to promote alertness and hopefully prevent crimes before they can take place. It is true, however, that spatial characteristics play an outmost role in the relationship between crime, spatial lighting and ICT, since small details, such as the location of trash bins, crevices and other three-dimensional information that provides shadows and hiding spots cannot be easily defined. Hopefully, the rapid influx of camera sensors with in-depth information can be of use, by mapping directly the UPS.

In an optimal scenario concerning surveillance and safety, each luminaire could incorporate such cameras. However, as the framework proposed in the present paper involves the surveillance of UPS and the human interaction therein, it is important to stress the attention paid to the ethical dimension of the development, deployment and implementation of smarter technologies in UPS, as well as the careful consideration of privacy concerns and ultimately the danger of harming the

UPS. Technological monitoring of UPS must ensure these protection mechanisms so that privacy is not threatened. The premise of the proposed methodology asserts that it is respected and protected following Martinez-Balleste et al. [105] and Santucci's work [85] on how sensitive information has to be protected. This includes "identity privacy" (to protect personal and confidential data), and "location and movement privacy" (to protect against the tracking of spatial behavior).

Despite the brighter prospect of AI to connect space, place, its lighting conditions, and crime, in addition to physical crimes potential harm can also be caused by the AI-enabled systems themselves in the following ways.

Cyber vulnerability—Data breach and security is not a new concern. The fear of cyber threats is also partially responsible for stigmatizing connectivity and data sharing. In 2018, the WannaCry cyber-attack cost the UK National Health Service (NHS) £92m [106,107]. Cyber vulnerability can expose cities to similar crimes. While critical and essential medical equipment such as pacemaker hacks surfaced years ago, recent hacks of Tesla cars brought concerns regarding cyber vulnerability back into the public eye [108,109]. Data management and cybersecurity in a smart city context have been explored in the literature, to a certain degree, using a few case studies of existing infrastructures in different parts of the world such as London, Barcelona, Singapore [110,111]. However, only limited risk assessments have been carried out in the literature on hyper-connected AI-enabled cities, as pointed out by Yigitcanlar et al. [112].

A connected city can emerge as a hacker's playground, as already seen via the "Krack attack" on Wi-Fi, a series of hacks on Amazon's Ring home security camera, CCTV camera hacks, and the list goes on [113]. While the use of AI to protect our cyberspace has a substantial scope for improvement, more integration could mean more vulnerability due to lack of technical capabilities, lack of understanding, lack of prioritizing cybersecurity, budget constraints, technological dependencies on other countries, the territorial reach of laws and regulations, lack of trust and transparency—all of which require continuous synchronized adaptation, based on circumstantial requirements [114]. Schneier portrays "a digital nightmare of hyper-connectivity" due to cyber vulnerability and the ways that policies can be designed to tackle them [115]. A real trial of cyber preparedness awaits, as the existing experiences are based on simulated environments and small-scaled testbeds [116]. Until then the fragmentation of data sources may offer an optimized safer solution, along with other best practices on security protocols and standards [117,118].

Data ownership—Although the social-media-driven cultural norm of "sharing" has made it acceptable to publicly share extremely private and personal information, the proposed data and image annotation may be agonizing and potentially harmful for a large portion of the population.

London city published its roadmap (www.london.gov.uk/smart-london) from the Mayor's office, engaging 33 local authorities along with other key organizations, to be transformed into a smarter city and a better place to live. The current infrastructure along with the associated challenges can be investigated through the publicly available datasets and data analytics (<https://data.london.gov.uk/>). Such a dynamic data space requires intense orchestration, as discussed by Gupta et al. [110]. The London Metropolitan Police has been recently further equipped with wearable cameras, gadgets, and analytics to collect evidence and to fight crime.

Augmented reality (AR)-enabled headsets for police, deployed in Shenzhen, Chengdu and Shanghai, are being utilized in the fight against COVID-19. The gadget is capable of identifying subjects along with their medical history.

Technological advancements may allow facial recognition software to perform real-time detection even using body-worn cameras. However, the usage of data, how data is being shared and to what extent, access to the data and how the shared data is being used requires standardization and monitoring, especially in a society where social inequity is an issue at stake.

A comprehensive approach, which is the focus of this paper, would require smarter and more integrative arrangements to automatically connect the dots within the ethical boundary by, of course, respecting personal privacy. Personal data within EU territory is protected by the General Data

Protection Regulation (GDPR), the most comprehensive regulation in the world to protect personal data; however, not free from limitations (<https://gdpr.eu/>). The philosophical grounds of data ownership are still under constant scrutiny [119,120]. Moreover, the rest of the world still needs to catch up with GDPR, and beyond.

Therefore, attention should be paid while linking data and sharing processed data, such as the proposed comprehensive framework (Figure 3), which may accidentally reveal information that was otherwise intended to be concealed/converted.

Usage of data—Automation in control and processing of data, and failure to ensure transparency in usage can lead to more crimes and injustice. The extent and acceptance of dataveillance need to be extensively evaluated, otherwise there is potential danger of turning cities into a virtual police state. Under the assumption that data coverage is no longer an issue for cities to be well-connected and fueled with IoTs, how much of it contributes to anticipatory governance and at what price will determine if AI will give birth to other kinds of evils.

While Kitchin [121] emphasized on data ethics within the smart urban designing context, a survey conducted by the software development and consulting company named Anaconda revealed one of the sources of ethical deficiency, as only 18% of data science students are learning AI ethics, whereas only 15% of the educators claimed to teach the subject in their class (<https://www.anaconda.com/state-of-data-science-2020>).

Moreover, The Alan Turing Institute highlighted that “AI systems that target, profile, or nudge data subjects without their knowledge or consent could in some circumstances be interpreted as infringing upon their ability to lead a private life in which they are able to intentionally manage the transformative effects of the technologies that influence and shape their development” [122].

Sustainable and resilient technologies must address the concerns about predictable risks from newly developed technologies for 5G (fifth-generation wireless technology) networks as well as unknown threats such as cyberweapons [123]. On the other hand, AI is as good as the data it learns from. We live in the reality of systematic racism and inequalities hardwired in our societal structure [124,125]. Therefore, bias and discrimination can be inherent to the data sources used [126], which causes the descriptive model to be flawed, hence the prediction becomes unreliable and preventative measures become ineffective or inadequate. Not only the ownership of data, but also autonomy in datafication raise questions regarding the responsibility and accountability of the processing made by AI agents. Some of the ethical challenges within smart city contexts were highlighted by Mark et al. for European cities in the Netherlands, Finland, Denmark and Germany [127].

On the one hand, the purpose of AI is to support the analysis of multi-modal, multi-dimensional overly complex data, while on the other hand, the explainability issue of AI has unlocked another sub-domain of research, i.e., explainable AI (XAI). The ongoing recent initiatives [128], such as the Future of Humanity Institute (University of Oxford) [129–131] or The Alan Turing Institute [122], may provide some answers regarding governable AI in the upcoming future that will help to shape the proposed framework while addressing the aforementioned concerns.

7. Future Work

In order to deal with the conflictual, multifaceted and complex nature of UPS, the proposed methodology could, at a later stage, require the mapping of urban spaces connected to crime, in order to classify them into typologies with common characteristics. Mapping is a way of recognizing, categorizing, as well as preventing or encouraging events. Mapping, nowadays, is enabled and enhanced by ICT and GIS. The implications of mapping in contemporary cities are both imperative and critical to their healthy growth. Technological developments, as Keith Hayward explains in his essay on the future of (spatial) criminology and research about public space [28], focus on crime mapping, surveillance and biometric security. Furthermore, AI can help with this classification, as well as pinpointing similar cases, so that more detailed and complete mapping of criminal areas can take place. Finally, a smart luminaire that can perform the actions stated in the proposed framework could

be designed in cooperation with the lighting industry. The authors firmly believe that such initiatives need to be developed with the support of stakeholders, such as local authorities and town planning organizations towards safe, resilient, smart and sustainable urbanities.

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